Adaptive Kalman Filters for Orbit Estimation of Navigation Satellites for DGPS Applications

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Overview

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7. Adaptive UKF based Orbit Estimation
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REFERENCES

Introduction

- Motivation
- Interoperable Differential SAT NAV systems
- Using GPS, GLONASS, GALILEO or other future satellites
- Several Aspects to Interoperability of Differential systems
- Estimation of Errors
- Focus on Orbit errors-Orbit Estimation

Kalman Filters

- Kalman filter is a sequential estimation problem normally based on the Innovations approach. The problem is normally stated as:
- Given a sequence of noisy observations to estimate the sequence of state vectors of a linear system driven by noise.
- Linear Model formulation

$$\mathbf{x}[n+1] = \mathbf{A}\mathbf{x}[n] + \mathbf{w}[n]$$

$$\mathbf{y}[n] = \mathbf{H}[n]\mathbf{x}[n] + \mathbf{v}[n]$$

Adaptive Kalman Filters

- **Kalman filtering: The Key issues**
  - **covariance matrices of the state and observation noises**
  - **noise statistics was assumed constant**
- **Noise Statistics may be UNKNOWN**

- **Adaptive Kalman Filtering facilitates**
- **Dynamic Estimation of Noise Statistics**
- **Suitable for Orbit Estimation**

Extended Kalman Filters

- Extended Kalman filter (EKF) provides an efficient method for estimates of the

1) state of a discrete-time, non-linear dynamical system.

- (The Filter is a recursive procedure to optimally combine noisy observations with predications)

2) estimating the parameters of a dynamic model (e.g. bias or drift in the dynamics)

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Unscented Kalman Filters(UKF)

- The unscented transformation (UT) is a method for calculating the statistics of a random variable which undergoes a nonlinear transformation.
- It is based on the fact that it is easier to approximate a probability distribution than an arbitrary nonlinear function.
- Does not suffer from some of pitfalls of the Extended Kalman filter

Orbit Modelling: Simulation

- Several approaches:
- Cartesian Coordinates
- Euler Hill Coordinates
- Lagrange planetary equations
- Hill Clohessy Wiltshire Linear model

- We choose the Cartesian approach and include only:

i) Earth oblateness effects, C20 and C22 terms

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Orbit Model

Dynamic model in orbiting Cartesian frame:

$$d\tilde{x}/d\tau = \tilde{x}',\ d\tilde{y}/d\tau = \tilde{y}',\ d\tilde{z}/d\tau = \tilde{z}', \quad (37a)$$

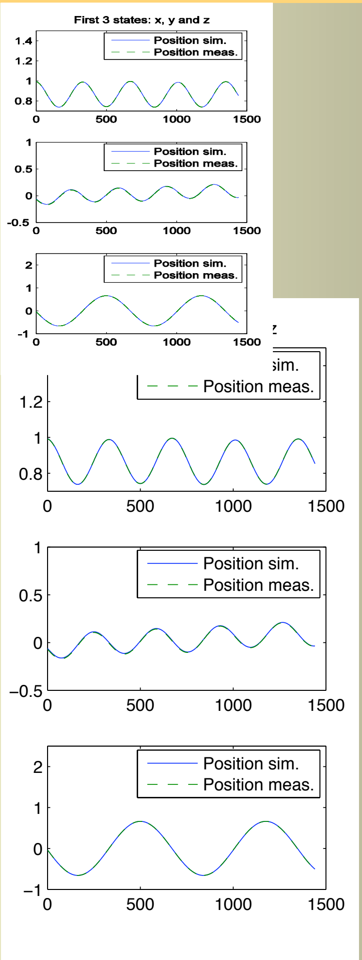
$$\frac{d\tilde{x}'}{d\tau} = -\frac{\mu_n}{\tilde{r}^3}\tilde{x} + \mu_n \frac{\partial \tilde{U}_2}{\partial \tilde{x}} + \tilde{x} + 2\tilde{y}' + \tilde{x}''_{res}, \quad (37b)$$

$$\frac{d\tilde{y}'}{d\tau} = -\frac{\mu_n}{\tilde{r}^3}\tilde{y} + \mu_n \frac{\partial \tilde{U}_2}{\partial \tilde{y}} + \tilde{y} - 2\tilde{x}' + \tilde{y}''_{res}, \quad (37c)$$

$$\frac{d\tilde{z}'}{d\tau} = -\frac{\mu_n}{\tilde{r}^3}\tilde{z} + \mu_n \frac{\partial \tilde{U}_2}{\partial \tilde{z}} + \tilde{z}''_{res}, \quad (37d)$$

where, $\mu_n = \mu/\Omega_n^2 r_s^3 = 1$, $\tilde{r} = \sqrt{\tilde{x}^2 + \tilde{y}^2 + \tilde{z}^2}$.

Orbital Response



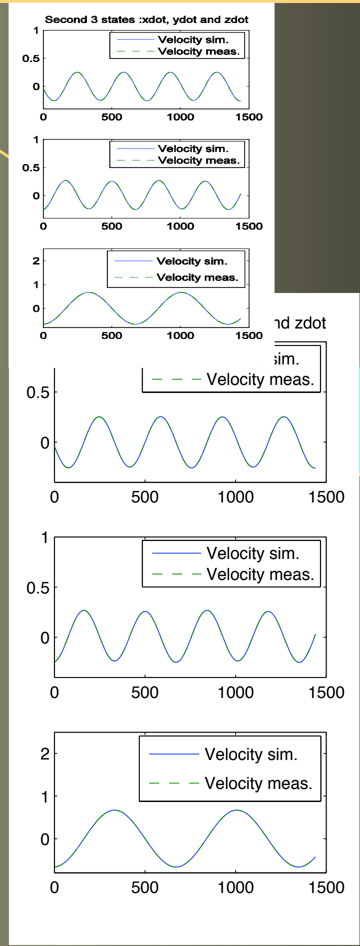


Fig. 1a. GLONASS satellite position prediction normalised to orbit radius versus time in minutes.

Fig. 1b. GLONASS satellite normalised velocity prediction versus time in minutes.

Orbital Response Errors

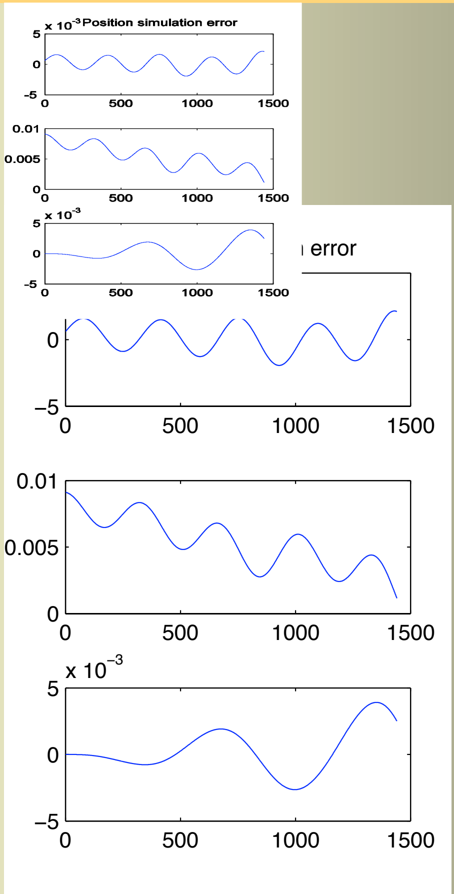


Fig. 2a. GLONASS satellite position prediction error versus time in minutes.

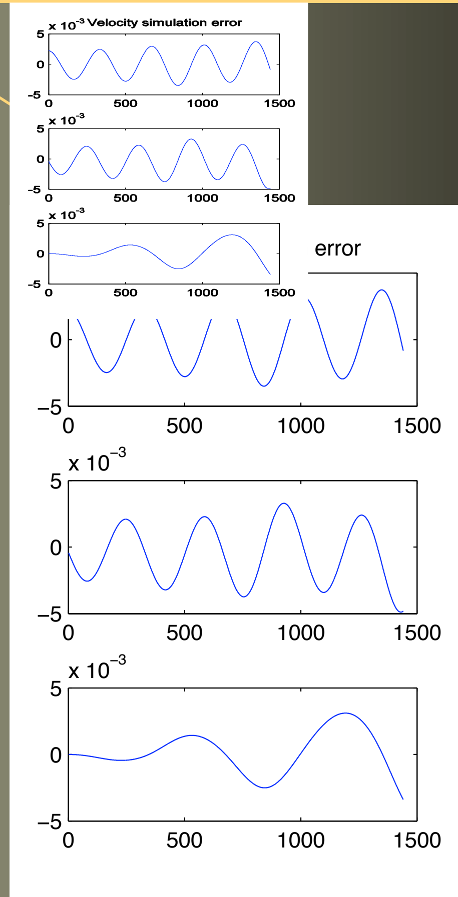


Fig. 2b. GLONASS satellite velocity prediction error versus time in minutes.

UKF Based Filtering: Error Estimates

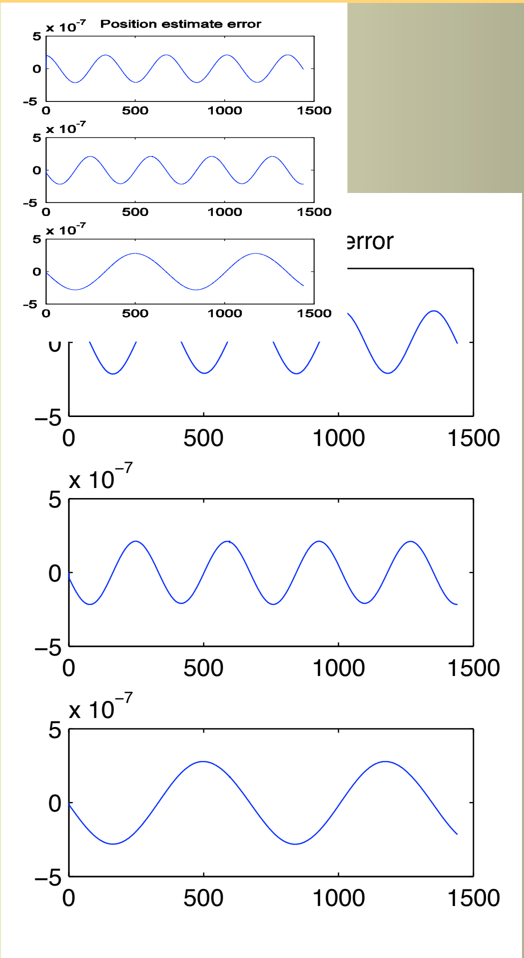


Fig. 3a GLONASS satellite UKF based position estimate error versus time in minutes.

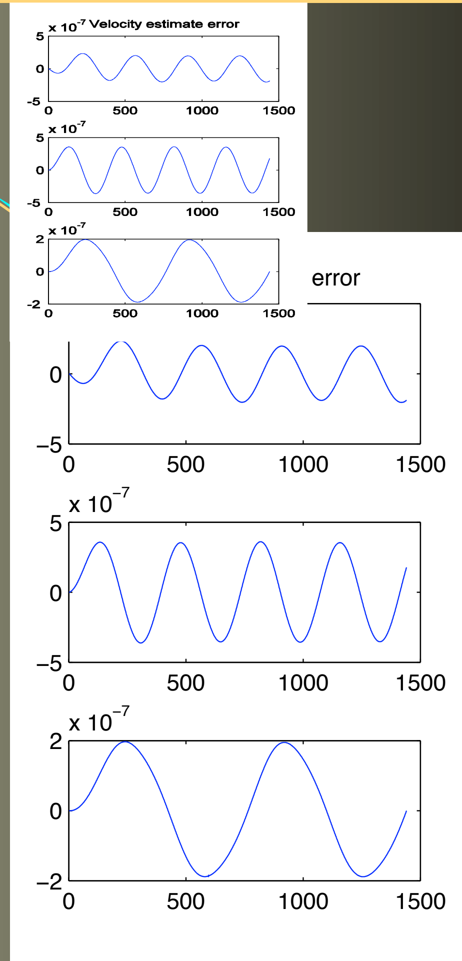


Fig. 3b GLONASS satellite UKF based velocity estimate error versus time in minutes.

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UKF Based Filtering: Pseudo-Range Error Estimates

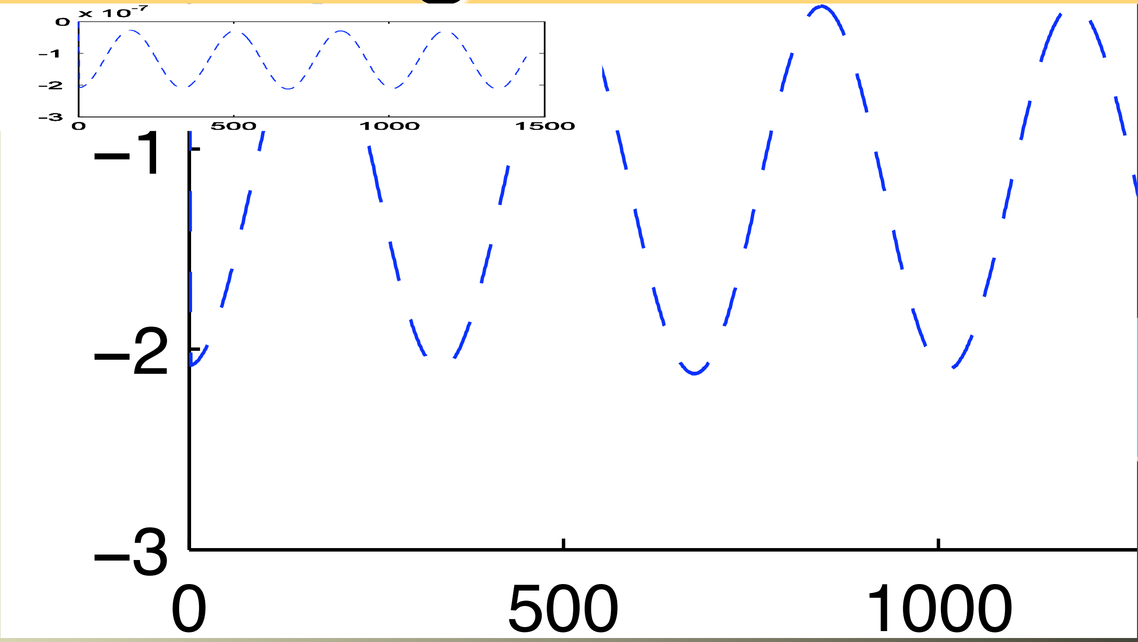

Fig. 4 GLONASS satellite UKF based pseudo-range estimate error versus time in minutes.

Maximum UKF based pseudo-range estimate error is below 10 m

Modified UKF Based Filtering: Pseudo-Range Error Estimates

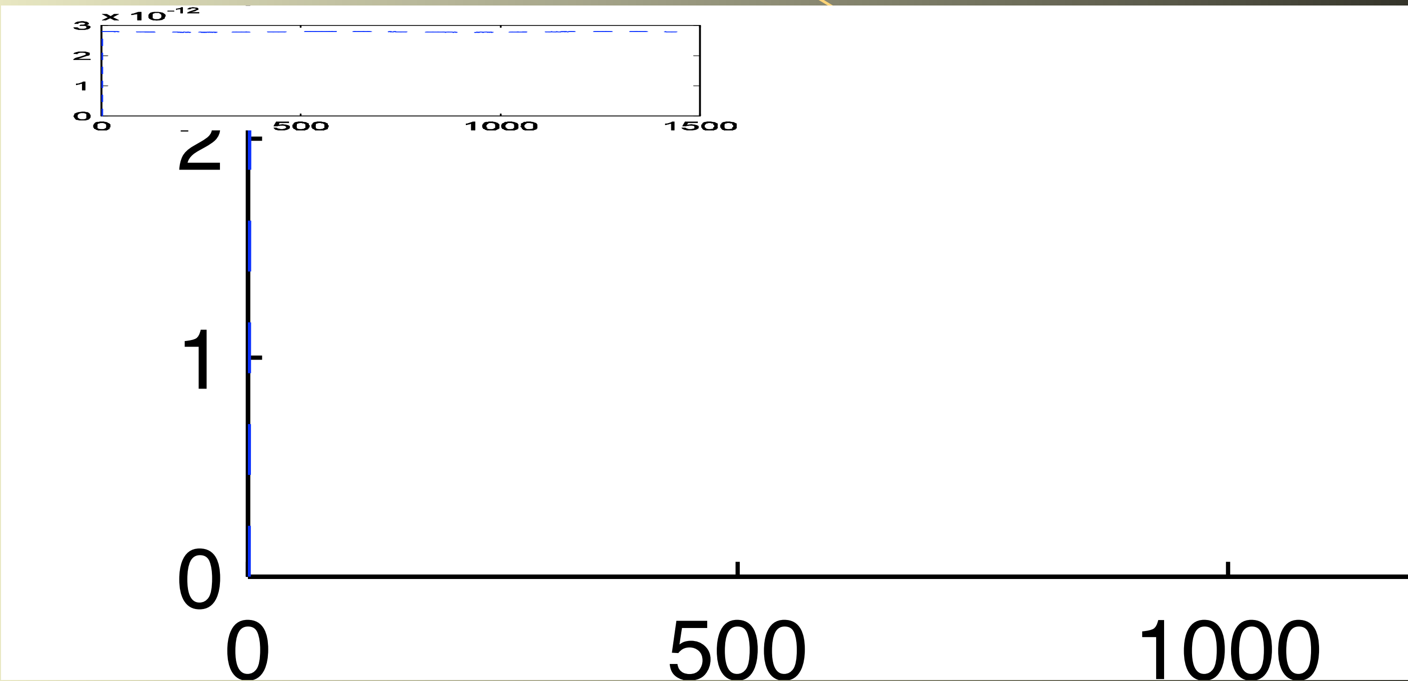

Fig. 6 GLONASS satellite modified UKF based pseudo-range estimate error versus time in minutes.

Maximum modified UKF based pseudo-range estimate error is below 1 mm

Adaptive UKF Filter: Error Estimates

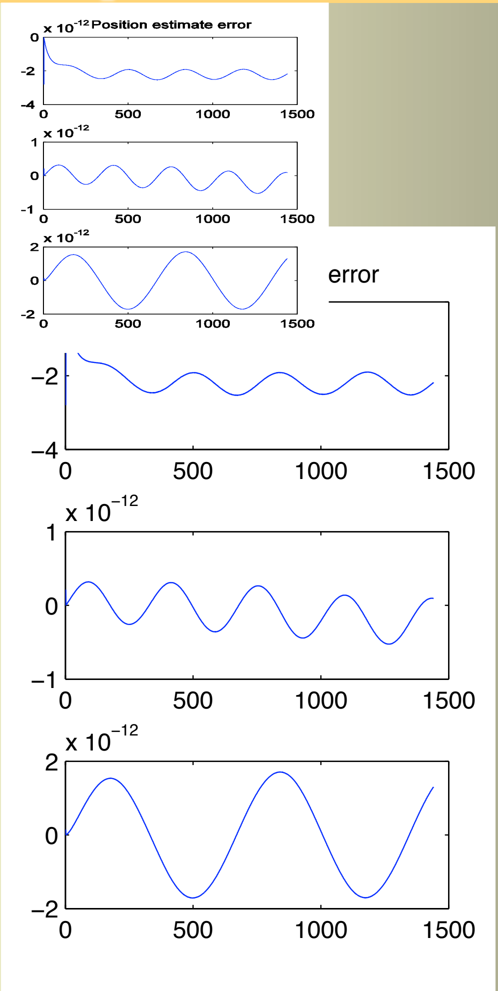

Fig. 7a GLONASS satellite adaptive UKF based position estimate error versus time in minutes.

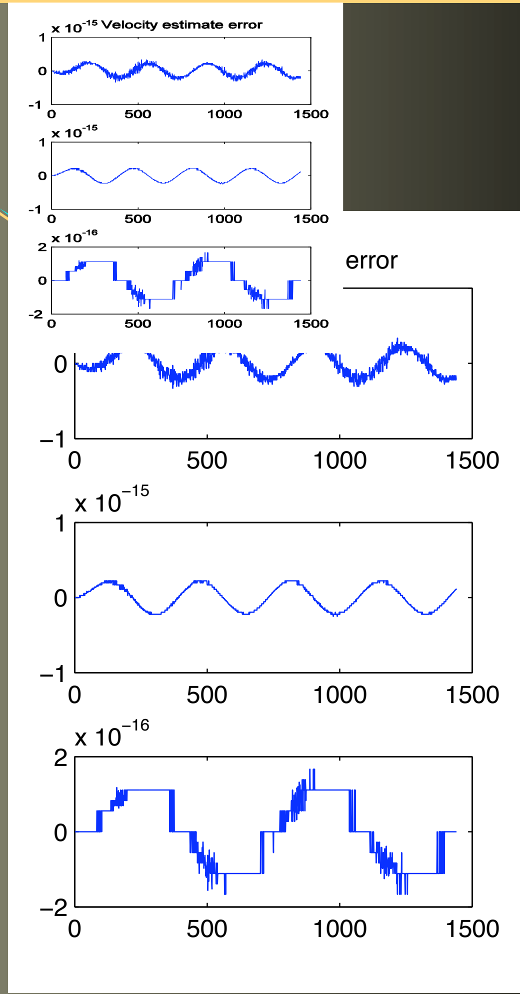

Fig. 7b GLONASS satellite adaptive UKF based velocity estimate error versus time in minutes.

Adaptive UKF Based Filtering: Pseudo-Range Error Estimates

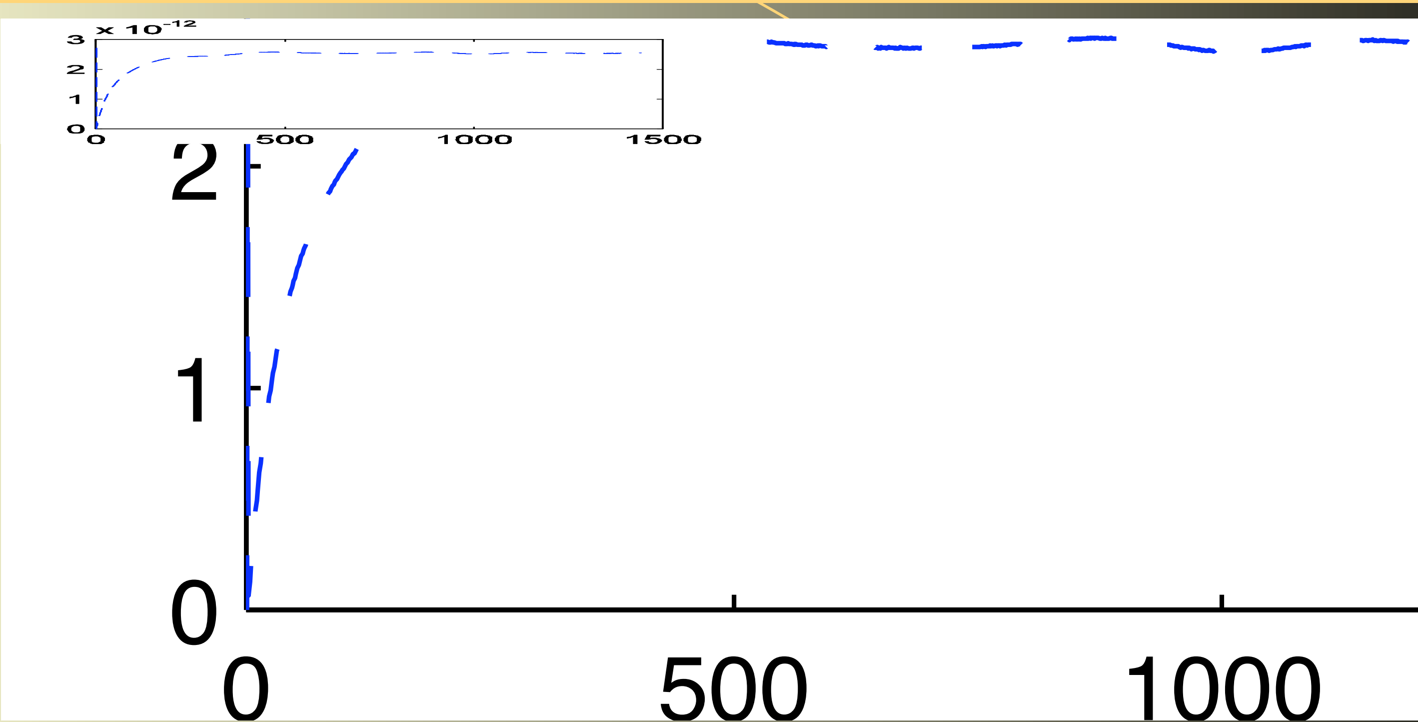

Fig. 8 GLONASS satellite adaptive UKF based pseudo-range estimate error versus time in minutes.

Maximum modified UKF based pseudo-range estimate error is below 1 mm

Conclusions

- The main reason for the better performance of the UKF is that the UT approximates the mean and the covariance to third order which is better than linearization.
- SVD improves performance of the UKF significantly
- The modified and adaptive UKF facilitate the use of arbitrary realistic models of the process and measurement noise statistics and thus give very good estimates of a navigation satellite's pseudo-range